Appendix A

HIGH FREQUENCY PASSIVE MICROWAVE RADIOMETRY OVER A SNOW-COVERED SURFACE IN ALASKA

This paper discusses the application of passive microwave (89 to 325 GHz) radiation data to identify clouds, vegetation and snow over central Alaska in April 1995.

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ABSTRACT

Millimeter-wave Imaging Radiometer (MIR) data (ranging in frequency from 89 to 325 GHz) collected from NASA ER-2 flights over Alaska in April 1995, are used to identify clouds, vegetation type, and snow cover. The procedure used is as follows : 1.) Determine whether a purely MIR-based cloud detection scheme is possible over a snow-covered surface; 2.) Analyze the influence of changing vegetation type on the brightness temperatures; and 3.) Compare completely snow-covered scenes with partially snow-covered and snow-free regions for cloudy and clear-sky periods to determine whether varying snow conditions affect the MIR data. Results show that the determination of cloudy pixels over a snow-covered surface is not possible using a simple brightness temperature threshold technique. Furthermore, it is concluded that while no statistical discrimination between specific vegetation classes can be made, statistical significance is obtained when the vegetation is grouped into two classes only, for example vegetated and barren. It is also shown that the state of the snow cover (complete coverage; melting; or patchy) has a distinct effect on these results.

INTRODUCTION

The Millimeter-wave Imaging Radiometer (MIR) records radiation emanating from the surface and atmosphere in nine frequency bands : 89, 150, 183.3+-1, 183.3+-3, 183.3+-7, 220, 325+-1, 325+-3, and 325+-8 GHz. The frequencies were chosen to match those of the Advanced Microwave Sounding Unit-B (AMSU-B) planned for NOAA operational satellites and the Earth Observing System (EOS) platform beginning in 2000. The MIR instrument was developed for atmospheric research, with the three channels centered about 183 and 325 GHz designed to study the atmospheric water vapor profile (Racette *et al.*, 1996). Other channels are less opaque and can provide some information about the surface. At an aircraft altitude of around 20,000 m the temperature sensitivity of the instrument is ≤ 1 K for all channels, and the pixel size is around 500 by 500 m at the nadir. The MIR instrument has been flown on several NASA ER-2 missions, including in Alaska in April 1995.

Between 31 March and 25 April 1995 the ER-2 flew on eight separate occasions over central to northern Alaska and the Bering Sea. The flight dates were April 3, 5, 6, 8, 13, 21, 23, and 24. Along with the MIR, the aircraft carried several other instruments including the Moderate Resolution Imaging Spectroradiometer (MODIS) Airborne Simulator (MAS), the Aerosol Particulate

Sampler (APS), the High Resolution Interferometer Sounder (HIS), and the Cloud Lidar System (CLS). The principal mission objective was to use remotely-sensed data to map snow and ice and make measurements of first-year and multi-year sea ice.

The surface cover in central Alaska is typically spruce, birch, aspen, mixed forest and muskeg while mountainous and northern regions are generally classified as either sparsely vegetated, barren, or permanent wetland. Over the period of the campaign, the snow conditions over Alaska varied quite markedly. By April 6 the snowpack in central Alaska was beginning to melt and that the cover was patchy by April 15 (Hall *et al.*, in press). In northern Alaska the snow cover remained continuous throughout April.

Two other datasets were used to determine cloudiness, snow cover, and surface vegetation cover. The first of these datasets is from the MAS. Using specific MAS channels and previously determined threshold tests, the cloud and snow cover were delineated and re-mapped to the resolution of the MIR data. In addition, vegetation data derived from a Normalized Difference Vegetation Index (NDVI) using Advanced Very High Resolution Radiometer (AVHRR) 1 km data, referred to as the International Geosphere Biosphere Programme (IGBP) land-cover classification (Belward and Loveland, 1995), was re-gridded to the MIR projection. There are seventeen land-cover categories in this classification, ranging from open water to evergreen needleleaf forests.

It is possible to detect clouds over water and snow-free land using data from the MIR instrument (Racette *et al.,* 1996). However, when the surface is covered with snow it becomes much more difficult to distinguish the relatively low brightness temperatures associated with the clouds with the similarly low brightness temperatures associated with a snow cover. Chang *et al.* (1987) explain that relatively high frequency microwave data (e.g. 92 GHz) is extremely sensitive to snow crystal scattering, however the high frequency data is also sensitive to atmospheric water vapor and clouds (Gasiewski, 1992). The MIR instrument measures mixed polarization signals, rather than horizontal and vertical, therefore polarization ratios or differences cannot be used to discriminate clouds. If horizontal and vertical polarizations were measured, it may be possible to more readily identify clouds, as surface emissions tend to be polarized while in general there is no polarization information from clouds.

Under clear-sky conditions, due to differences in recorded high frequency brightness temperatures between different species of vegetation, Hall *et al.* (1995) suggest that surface vegetation may be detectable. In addition, the MIR data may be used to estimate snow cover characteristics such as melting snow and snow-covered area. The presence of liquid water transforms a snowpack from one which scatters microwave radiation to one which absorbs and re-emits it (Ulaby and Stiles, 1980). This dramatically increases the brightness temperature (T_B) to that approaching the physical temperature of the medium. Also, Rango *et al.* (1979) show that when the snowpack is dry there is sufficient contrast in the brightness temperature range between snow and bare ground, due to a lower dielectric constant and the effect of scattering in snow, for estimation of snow-covered area.

The objective of this study is to examine the utility of high frequency passive microwave data, recorded by the MIR instrument flown over Alaska in April 1995, for the purpose of identifying clouds over a snow-covered surface, distinguishing differences in land-cover, and monitoring snowpack parameters such as melting snow and snow-covered area. The MIR data was used in combination with the MAS and IGBP Land-cover datasets to evaluate the relationships between microwave brightness temperatures and cloud, snow, and vegetation cover.

1. AN INITIAL LOOK AT THE MIR DATA

Figure 1 shows a brightness temperature map at 89 GHz for 13 April 1995, for central Alaska. Some of the surface features are clearly visible. The border between yellow and green (at around 230 K) appears to delineate the transition between vegetation types or the presence or absence of snow, perhaps as a function of elevation. In addition, in the bottom and bottom-right sections of the image there are some regions of much lower brightness temperatures (< 200 K) which may represent clouds. Features such as these will be investigated in the following sections. Figures 2 and 3 show time series plots of the average brightness temperature across each scan (the average of 57 pixels per scan line) for 89 and 220 GHz, respectively. Variability along these time series plots is related to the surface and atmospheric effects stated above. The 220 GHz data (1.4 mm wavelength) is more sensitive to atmospheric phenomena compared with 89 GHz (3.4 mm) because the atmospheric contribution to the upwelling radiation is larger for shorter wavelengths (Schanda and Hofer, 1977).

2. CLOUDY VERSUS CLEAR PIXELS

To test whether clouds can be detected over a snow-covered surface, several flight lines from the Alaska mission were analyzed. A multi-spectral cloud-masking algorithm (Ackerman *et al.*, 1997), derived from MAS data, is used to determine the presence or absence of cloud. Briefly, the cloud-masking algorithm initializes each scene as cloudy and then several threshold tests are performed to determine which pixels are clear. Based on known relationships, cloud type can also be distinguished as either low or high cloud. There are also flags for day or night, sun glint, a snow or ice background, a land or water background, shadow, and an obstructed field of view (by smoke or dust, for example).

Figure 4 is a plot of the brightness temperatures at 89 GHz versus pixel number for the first section of data for the flight on 3 April 1995. The distance covered on the ground is approximately 3.3 km, and the ground is completely snow covered. The lighter asterisks represent the brightness temperatures of all of the pixels in this section of the data record. There are a total of 18,870 pixels. Plotted over these values is the subset of pixels which has been determined to be cloudy, using the MAS cloud-masking algorithm. These cloudy pixels are delineated as darker crosses, and there are a total of 2,912 pixels, or 15.4% of the total number of pixels.

From this figure it appears as though the cloudy pixels generally have a lower brightness temperature than the cloud-free pixels. The number of cloudy pixels was compared with the number of cloud-free pixels using a brightness temperature range between 200 and 220 K, where the majority of the cloudy pixels are located,. The total number of cloudy pixels within this brightness temperature range was 2,769. The total number of cloud-free pixels within this range, however, was 12,000. Hence, it appears that while the brightness temperature of clouds may be lower than some clear-sky pixels, there are a substantial number of clear-sky pixels within the same brightness temperature range. These results were replicated for each of the flights of the Alaska mission.

It may be concluded that for these flights over Alaska, while it is possible to visually identify some clouds over a snow-covered surface in an MIR image, it is not possible to discriminate between clouds and clear sky pixels statistically using the MIR data. This is because while some clouds, particularly low clouds, may be distinguishable from the snow-covered background, the brightness temperature range of all clouds is very similar to that of the snow.

3. RELATIONSHIP BETWEEN VEGETATION AND BRIGHTNESS TEMPERATURE

Hall *et al.* (1995), using the same Alaskan dataset, conclude that the MIR data show brightness temperature patterns that are related to land-cover. They state further that the major delineation appears along the boundary between black spruce forest and the meadow dryas. Coniferous trees emit more microwave radiation than do tundra or dryas vegetation, and this is one explanation for the higher brightness temperatures in the black spruce forests (Hall *et al.*, 1995). These findings were replicated in this study. When looking at the brightness temperature data alongside the IGBP vegetation data (both in the same projection and georeferenced according to latitude and longitude), the boundary between forest and shrubland in the MIR data can be easily identified. However, when the brightness temperatures were plotted against the vegetation categories for the April 3rd flight for cloud-free pixels only (Figure 5), it is not possible to discriminate between the vegetation categories.

The April 3rd flight, though, traversed several degrees of latitude and the surface maximum air temperature ranged from 10°C (in Fairbanks : 64.5°N) to -14°C (in Prudhoe Bay : 70.4°N). It is possible that these large air temperature differences have masked out any relationship between brightness temperature and vegetation. Therefore, a second flight was analyzed, that of April 13th, which only covered a small area in the Fairbanks region, and hence had much less of an air temperature range. The results from this analysis, however, mirrored those of April 3rd (Figure 6). Using the normalized difference between brightness temperatures at 89 and 150 GHz (89 - 150 / 89 + 150) and between 89 and 220 GHz (89 - 220 / 89 + 220) as a means of reducing the influence of the air temperature, also resulted in insignificant findings.

Again, as with the cloud analysis, it is concluded that although changes in the IGBP vegetation type are viewable in the MIR data, statistically significant relationships cannot be determined. This may be due to the presence of the snow cover. On April 3rd snow was continuous over almost all of the flightline. It is possible that the microwave emission and scattering from the snowpack masked the differences caused by different vegetation. Also, as the snowpack was actively melting in central Alaska by April 13th, it is equally possible that the microwave emissions from liquid water, either in the snowpack or in the top layer of soil, confuse the relationship between land-cover type and brightness temperature.

4. ANALYSIS OF A PARTIALLY SNOW-COVERED SCENE

Chang *et al.* (1987) conclude that brightness temperature data at 92 GHz can be used to discriminate between snow-covered and snow-free land when clouds are not present. A "first look" of the MIR data from the Alaska 1995 mission verifies this result. Thus, using the MODIS snow mapping algorithm (Klein *et al.*, in press) on the MAS data to delineate the snow boundary, and using the MAS cloud-masking algorithm to determine cloud-free pixels only, an analysis of the MIR data for April 13th was performed. This day was chosen because the MODIS snow-mapping algorithm shows patchy snow around the Fairbanks region. Figure 7 shows the same type of plot used to test the relationship between vegetation and brightness temperature. However, in addition to showing the variation between vegetation categories, this plot also separates out snow-free pixels as darker crosses, and snow-covered pixels as lighter asterisks.

From Figure 7 it can be seen that the snow-free pixels have a smaller brightness temperature range for many of the vegetation categories, and have fewer lower brightness temperatures compared with the snow-covered pixels. The same results were obtained using 150 and 220 GHz data. Although, when the number of snow-covered pixels which have brightness temperatures in the same range as the snow-free pixels are compared, it is clear that a statistical differentiation between snow-covered and snow-free surfaces could not be accomplished. Table 1 shows the results of this analysis. Upon comparison of the third and fourth columns of Table 1, it can be seen that there are always a greater number of snow-covered pixels in the same brightness temperature range than there are snow-free pixels.

Once again, despite some indication that snow-free pixels tend to have higher brightness temperatures, no statistical discrimination is possible. Normalized difference ratios were again used to reduce the influence of the air and surface temperature with no improvement in the statistical significance. As previously mentioned, these results may be affected by the presence of liquid water either in the snowpack or in the top layer of the soil. To reduce this problem, future missions may consider nighttime flights when much of the meltwater has re-frozen.

5. ANALYSIS OF A COMPLETELY CLOUD-COVERED SCENE

The flight on 21 April 1995 was almost entirely cloud covered. It is during conditions such as this that microwave data should be most useful, to supplement the visible data. Surface features are clearly visible in the MIR data for this day. Can the vegetation type or the presence of snow cover be detected?

Figure 8 is a side-by-side comparison of MIR, MAS, and IGBP vegetation data for a section of the April 21st flightline. The first three columns represent data from the 89, 150, and 220 GHz channels of the MIR instrument. The scale (not shown here) is the same as for Figure 1. Surface features are apparent in the first three columns. The fourth column is the Channel 2 (0.627 microns) reflectance data from MAS. Note that the width of this and the next two columns is a little less than the MIR data, due to the different scan angles of the instruments (MIR = 100°, MAS = 85.92°). The Channel 2 data are a little blurred, particularly in the middle section, due to the presence of a thicker cloud cover.

The fifth column depicts the location of snow (in white) as mapped by the MAS snow mapping algorithm. Because the algorithm is based on optical data, no snow will be mapped under thick cloud cover. The sixth column shows the cloud cover as prescribed by the MAS cloud-masking algorithm. The scene is 100% cloud covered. In blue are pixels which have been designated high cloud only, while the yellow pixels represent both high and low clouds and red pixels denote low cloud only. Lastly, the vegetation is mapped. The pixels colored red through dark green are forested (red = evergreen needleleaf; yellow = deciduous broadleaf; dark green = mixed forest). The light green represents closed shrublands and the light blue depicts open shrublands. The purple-colored area is permanent wetland.

There appears to be a distinct relationship between the MIR brightness temperatures and the vegetation type. When data from the entire flight was analyzed, though, no such relationship could be determined (Section 3). Similarly, relationships between cloud cover or snow cover and the MIR data were statistically insignificant. However, concentrating only on the area shown in Figure 8 reveals that higher brightness temperatures are loosely associated with denser vegetation. Furthermore, when all the forest categories were grouped together, and likewise all the non-forested vegetation categories grouped together, the difference between the two groups at all three MIR channels was statistically significant (t-test, significance level $< 0.1\%$). The mean T_B (89 GHz) for the combined forested pixels is 247.6K, while the mean for the non-forested pixels is 234.9K.

This result suggests that the high frequency MIR data can be used to discriminate between some surface features such as between forest and shrubland, even under cloudy conditions. The following section investigates this result further, by analyzing the entire flightlines of April 3rd, 13th, and 21st.

5. ANALYSES OF BINARY CLASSIFICATIONS OF VEGETATION

Based on the previous result, the MIR brightness temperature data for the entire 21 April 1995 flightline were analyzed by testing for a difference between the means of the forested pixels and the non-forested pixels. Again, the t-test was significant (significance level < 0.1%) with the mean $T_{B(Forest)}$ = 235.1K (89 GHz), and the mean $T_{B(Other)}$ = 223.8K (89 GHz). However, Figure 9, which shows the histograms of the two vegetation groups, indicates that the non-forested group is bimodal and that some of the non-forested pixels clearly belong in the forested category. Hence, beginning with "closed shrublands," vegetation classes were systematically removed from the non-forested category and added to the forested category. With every iteration the second peak in the non-forested histogram decreased while the first peak increased. The best discrimination between brightness temperatures for April 21st is shown as Figure 10, where the solid line represents all vegetated surfaces and the dotted line represents barren land (mean $T_{B(Vegetated)}$ = 233.5K (89 GHz), mean $T_{B(Barren)}$ = 215.7K (89 GHz)). This result shows that brightness temperature differences are greatest in response to the presence or absence of vegetation, rather than the boundary between, for example, forest and shrublands.

To test this result, data from April 13th and April 3rd were analyzed. Figures 11 and 12 represent the histograms of forested versus non-forested, and vegetated versus barren for the April 13th flight. On this day very little discrimination can be made between either of the vegetation groupings. It is argued that this is a direct function of the presence of melting snow. Hall *et al.* (in press) show that there was rapid melting in the Fairbanks region between the 6th and 15th of April. It is therefore likely that the presence of liquid water in the snowpack is masking the differences in the microwave signal caused by the vegetation.

The histograms for April 3rd are shown as Figures 13 and 14. Figure 13, which represents delineation between forests and non-forests, is almost the complete opposite of Figure 9, the same vegetation groupings for April 21st. In Figure 13 it is the forest category which is bimodal and it is clear that some of these data belong in the non-forested category. Thus, beginning with "mixed forest," the vegetation groups were re-classified by removing classes from forested and adding them to non-forested. Figure 14 represents the best discrimination between vegetation types. Here, the solid line is evergreen needleleaf forest only and the dotted line is everything else. The difference between the two means is highly significant (significance level < 0.1%), with the mean $T_{B(Evergreen)}$ = 233.8K (89 GHz) and the mean $T_{B(Other)}$ = 222.0K (89 GHz). This result highlights the impact of a continuous dry snow cover and the ability of the MIR instrument to view the snow cover. In all the vegetation classes except evergreen forest, the sensor can detect the presence of snow on the surface, and the scattering from this snow is effectively reducing the brightness temperature. However, the denser canopy of the evergreen forest is able to mask much of the snowpack scattering, in addition to contributing to the relatively warmer brightness temperatures through emission from the trees themselves.

Therefore, the condition of the snowpack is vital in determining the best binary delineation between vegetation types, based on high frequency microwave data. If the surface is almost snow-free, then the MIR data best delineate the boundary between vegetated and barren land. When the snow is melting the microwave signal is swamped by the presence of liquid water and little discrimination between vegetation types is possible. If a continuous coverage of dry snow is present then high frequency microwave data can be used to effectively delineate between evergreen trees and other vegetation classes.

DISCUSSION AND CONCLUSIONS

Previous studies have indicated that high frequency (greater than 80 GHz) microwave data may be useful in the identification of such phenomena as clouds, snow, and vegetation. One of the main difficulties, as this study shows, is the identification of clouds over a snow-covered surface due to very similar brightness temperature values. If the MIR recorded polarized data, then such discriminations may be possible using a polarization ratio or difference. A further consideration for future missions using the ER-2 is a nighttime flight over a patchy snow cover. This may reduce the influence of melting snow on the brightness temperatures and enhance the differences between snow-covered and snow-free land. Satellite-derived microwave maps of snow cover use nighttime orbits to ensure snow is as dry as possible.

Results from this study confirm other reports that vegetation types can be visually identified using high frequency brightness temperature data. However, it is concluded that no statistical relationship is present between brightness temperature and the IGBP land-cover classes, hence it is not possible to objectively detect such surface features under snow-cover conditions. Alternatively, when the vegetation classes were grouped into binary classifications, highly significant results were produced. This suggests that there is an underlying relationship between brightness temperature and surface features, but that it is only statistically significant when the vegetation groups are simplified.

A major implication of this research concerns the estimation of snow-covered area, snow depth, and snow water equivalent using passive microwave radiation data. It has been shown by several authors (e.g. Chang *et al.*, 1997) that forest cover has a significant effect on brightness temperatures in the range 18 GHz to 37 GHz. Tait (in press) made several land-cover divisions including forested and unforested as a means of enhancing the snow cover signal. This study shows, however, that such a division may not necessarily represent the best binary land-cover delineation. It is shown here that the optimum vegetation discrimination is strongly related to the condition of the snow cover. This should be considered for future studies of passive microwave estimates of the snow cover.

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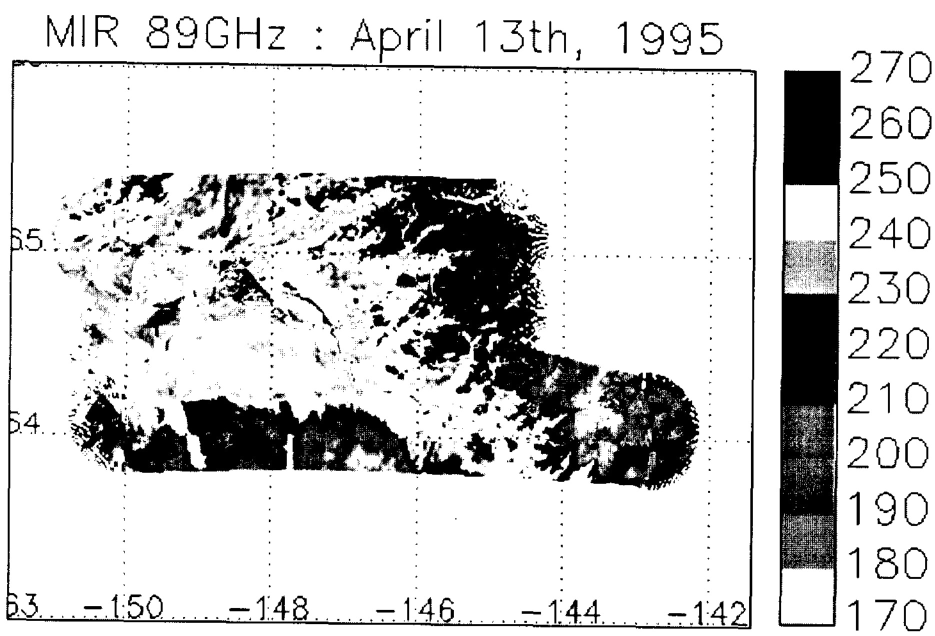
LIST OF FIGURES

Table 1 : Number of snow-covered and snow-free pixels for April 13, 1995.

VEG TYPE	# PIXELS	# SNOW-FREE PIXELS	# SNOW-COVERED PIXELS ($T_B > T_{Bc}$)	T_B CUTOFF (T_{Bc})
Snow or Ice	241	10	39	245*
Perm. Wetlands	14373	322	13832	225
Woody Savannas	47209	2310	43072	212
Open Shrublands	10680	959	9260	210
Closed Shrublands	17453	1630	15247	225
Mixed Forest	265532	12350	243678	210
Dec. Broadleaf	79612	7250	72143	245
Evgn. Needleleaf	158240	11127	146070	235

* For this ground-cover category (permanent snow or ice) the T_B values for snow-free pixels were colder than for snow-covered pixels.



MIR 89GHz : April 13th, 1995
65
64
63
−150
−148
−146
−144
−142
270
260
250
240
230
220
210
200
190
180
170

Fig 1

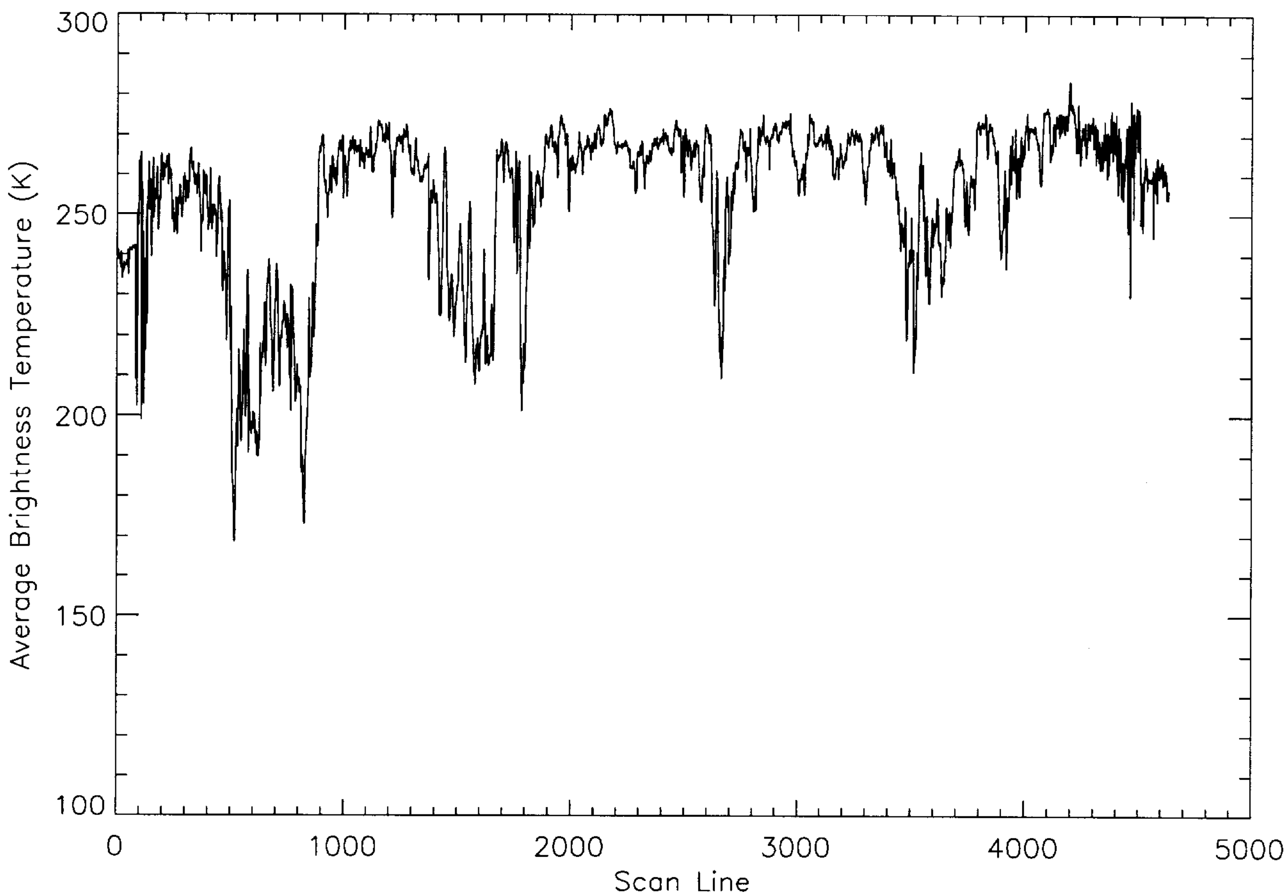
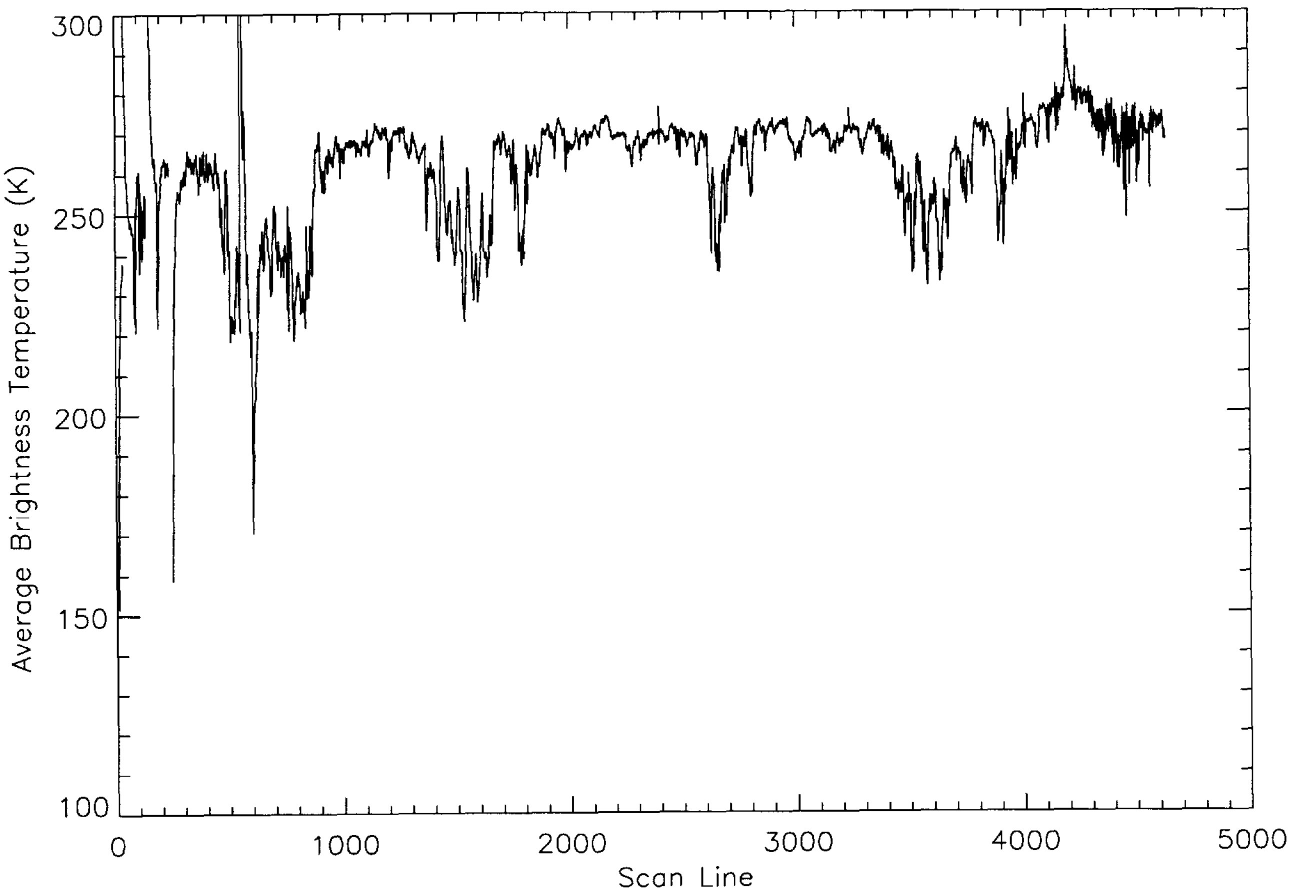
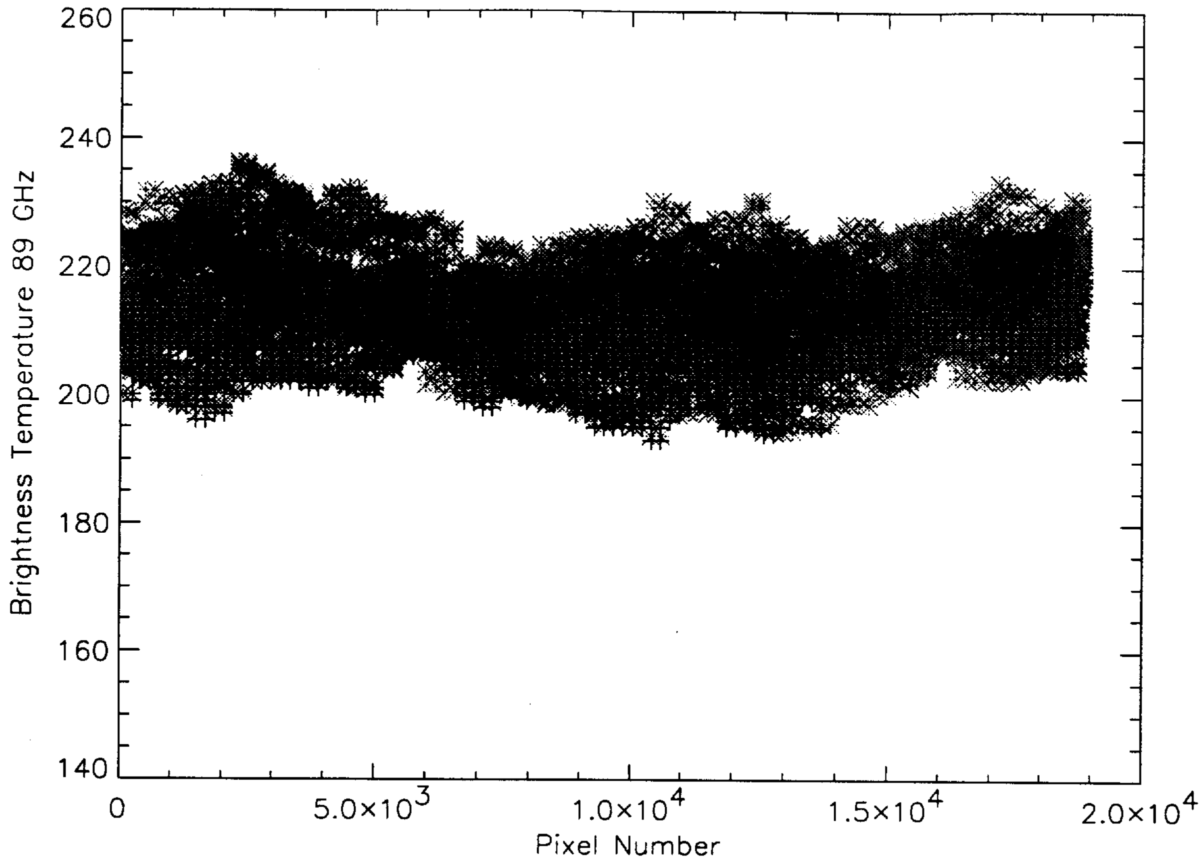

Average Brightness Temperature (K)
300
250
200
150
100
0
1000
2000
3000
4000
5000
Scan Line

Fig 2



300
250
200
150
100
Average Brightness Temperature (K)
0
1000
2000
3000
4000
5000
Scan Line

Fig 3



260
240
220
200
180
160
140
Brightness Temperature 89 GHz
0
5.0×10^3
1.0×10^4
1.5×10^4
2.0×10^4
Pixel Number

Fig 4

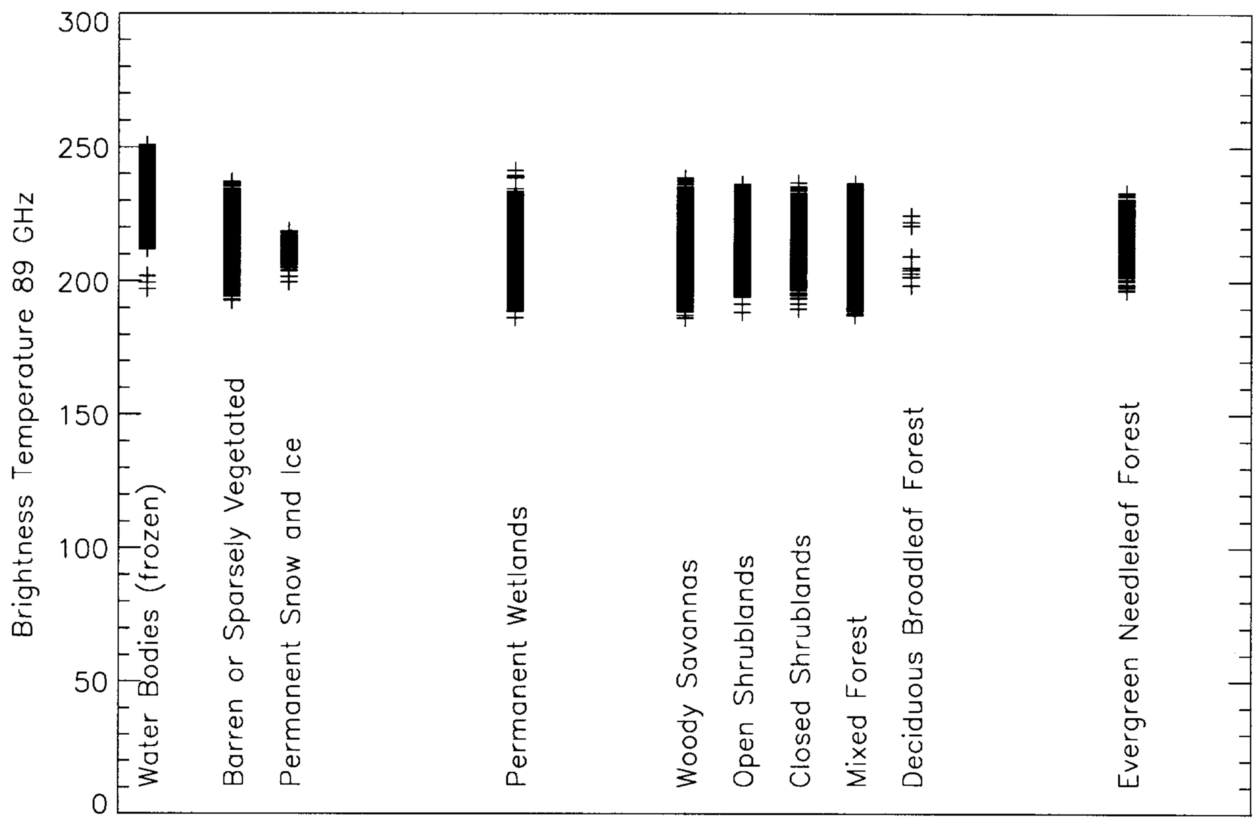
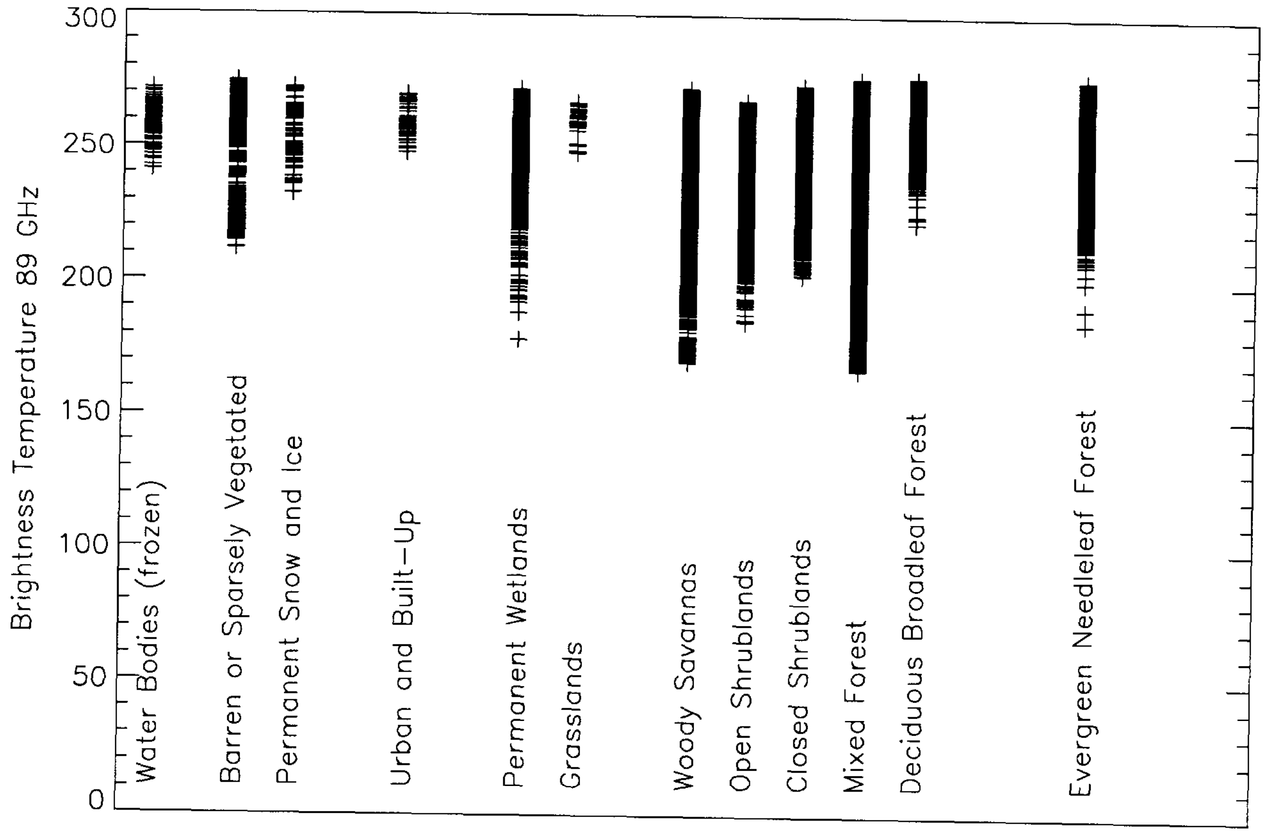
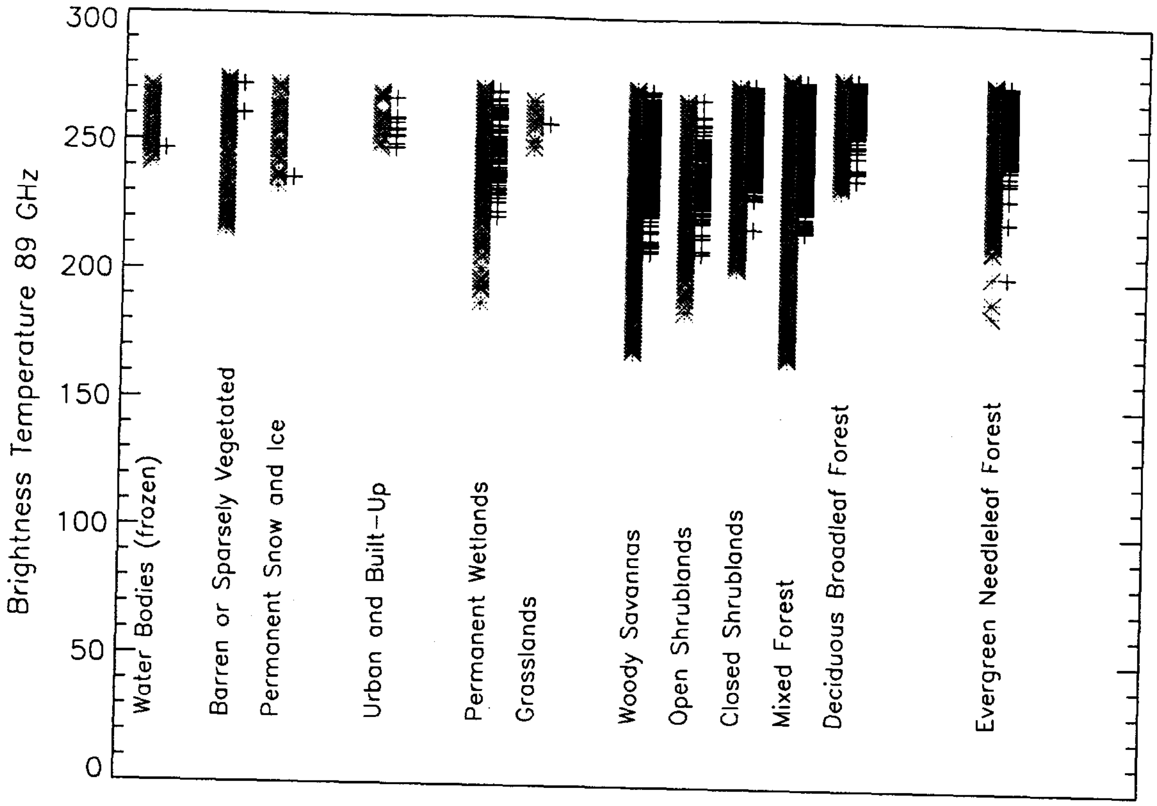

Brightness Temperature 89 GHz
300
250
200
150
100
50
0
Water Bodies (frozen)
Barren or Sparsely Vegetated
Permanent Snow and Ice
Permanent Wetlands
Woody Savannas
Open Shrublands
Closed Shrublands
Mixed Forest
Deciduous Broadleaf Forest
Evergreen Needleleaf Forest

Fig 5



Brightness Temperature 89 GHz
300
250
200
150
100
50
0
Water Bodies (frozen)
Barren or Sparsely Vegetated
Permanent Snow and Ice
Urban and Built-Up
Permanent Wetlands
Grasslands
Woody Savannas
Open Shrublands
Closed Shrublands
Mixed Forest
Deciduous Broadleaf Forest
Evergreen Needleleaf Forest

Fig 6


Brightness Temperature 89 GHz
300
250
200
150
100
50
0
Water Bodies (frozen)
Barren or Sparsely Vegetated
Permanent Snow and Ice
Urban and Built-Up
Permanent Wetlands
Grasslands
Woody Savannas
Open Shrublands
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Mixed Forest
Deciduous Broadleaf Forest
Evergreen Needleleaf Forest

Fig 7

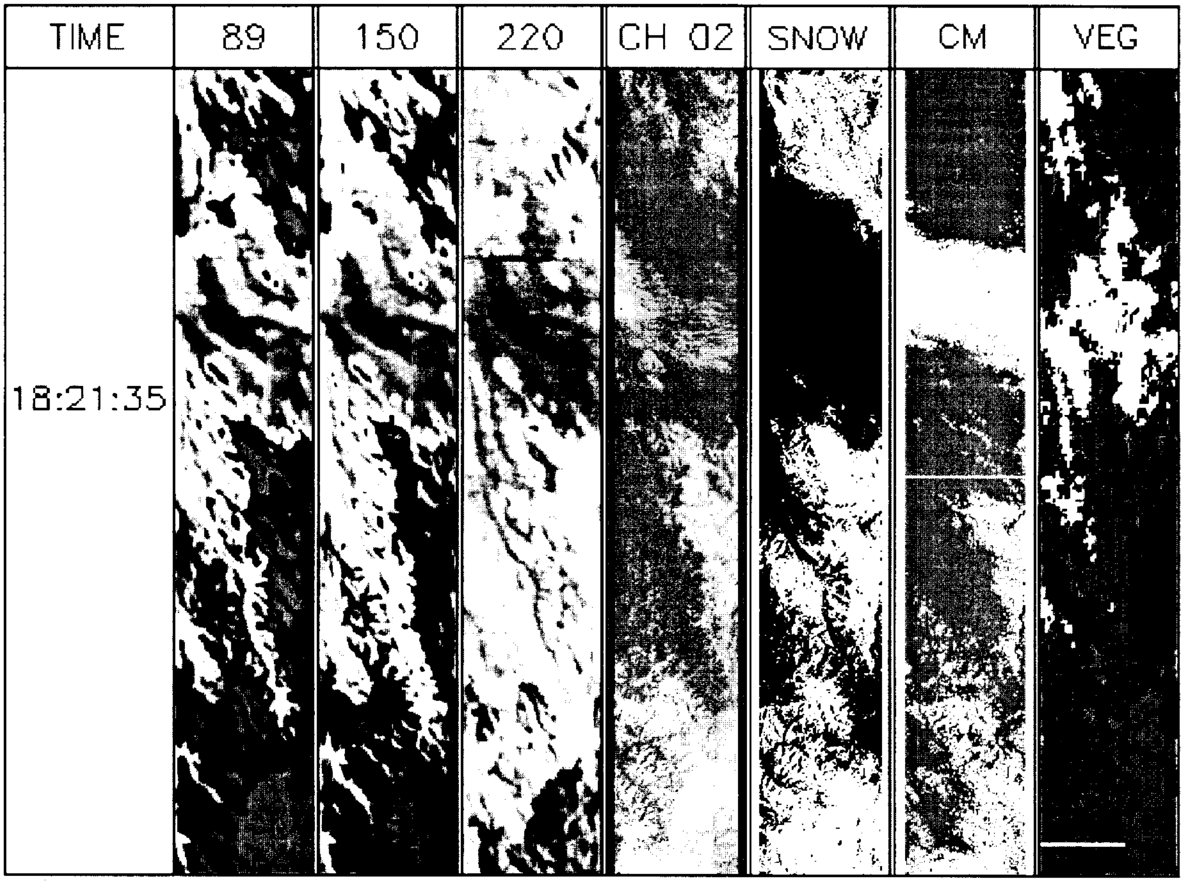

Figure 8

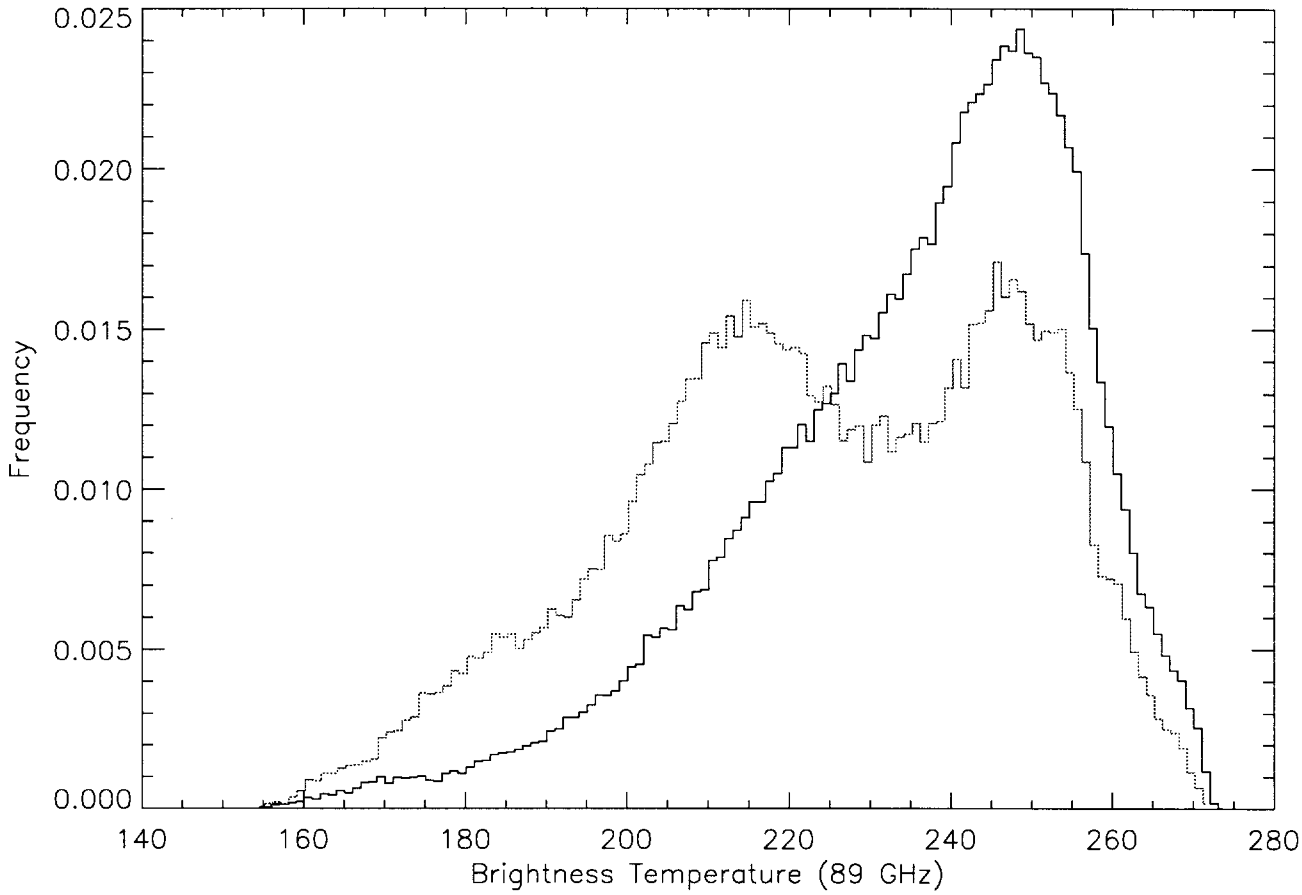
0.025
0.020
0.015
0.010
0.005
0.000
Frequency
140
160
180
200
220
240
260
280
Brightness Temperature (89 GHz)

Fig 9

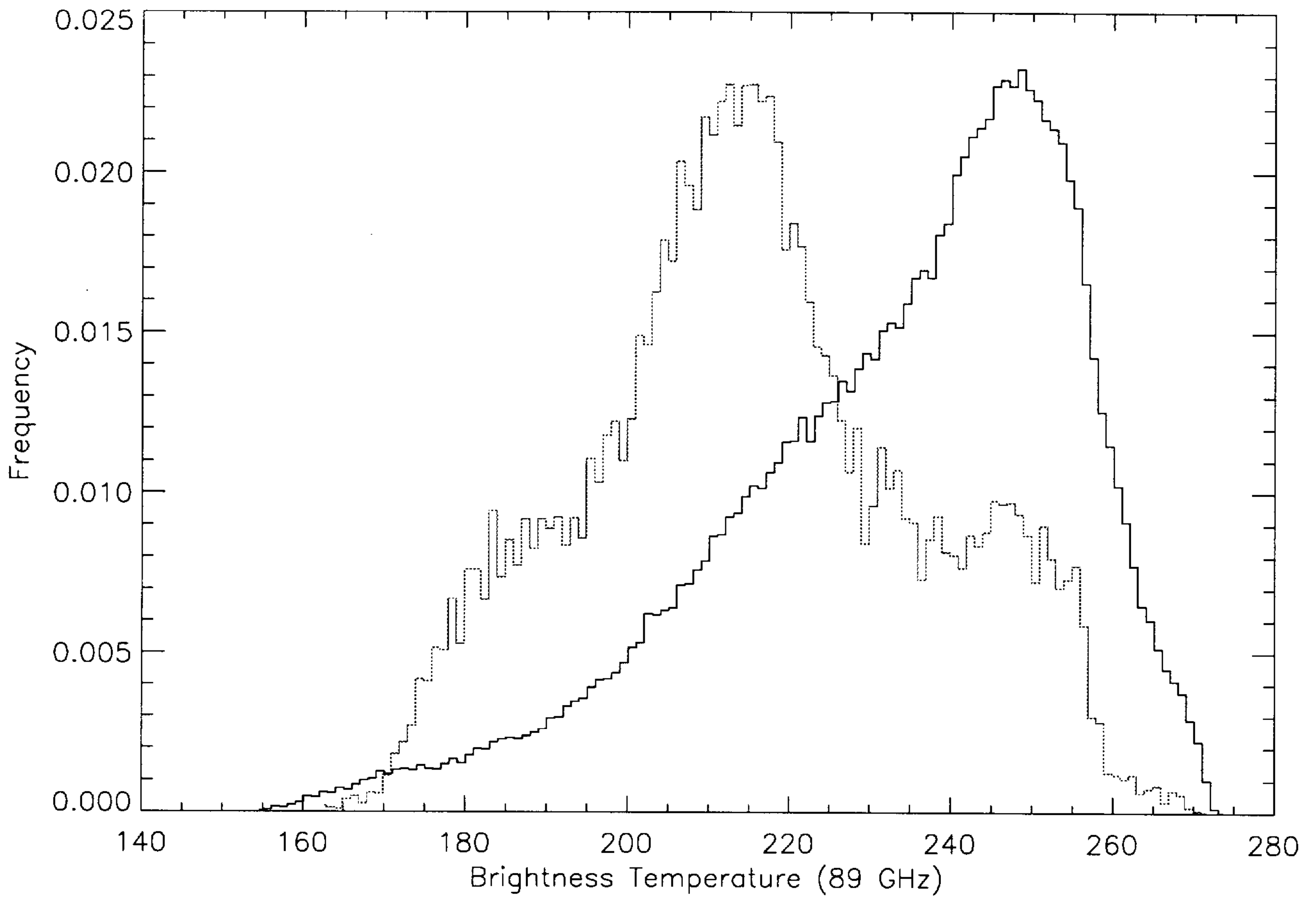
0.025
0.020
0.015
0.010
0.005
0.000
Frequency
140
160
180
200
220
240
260
280
Brightness Temperature (89 GHz)

Fig 10

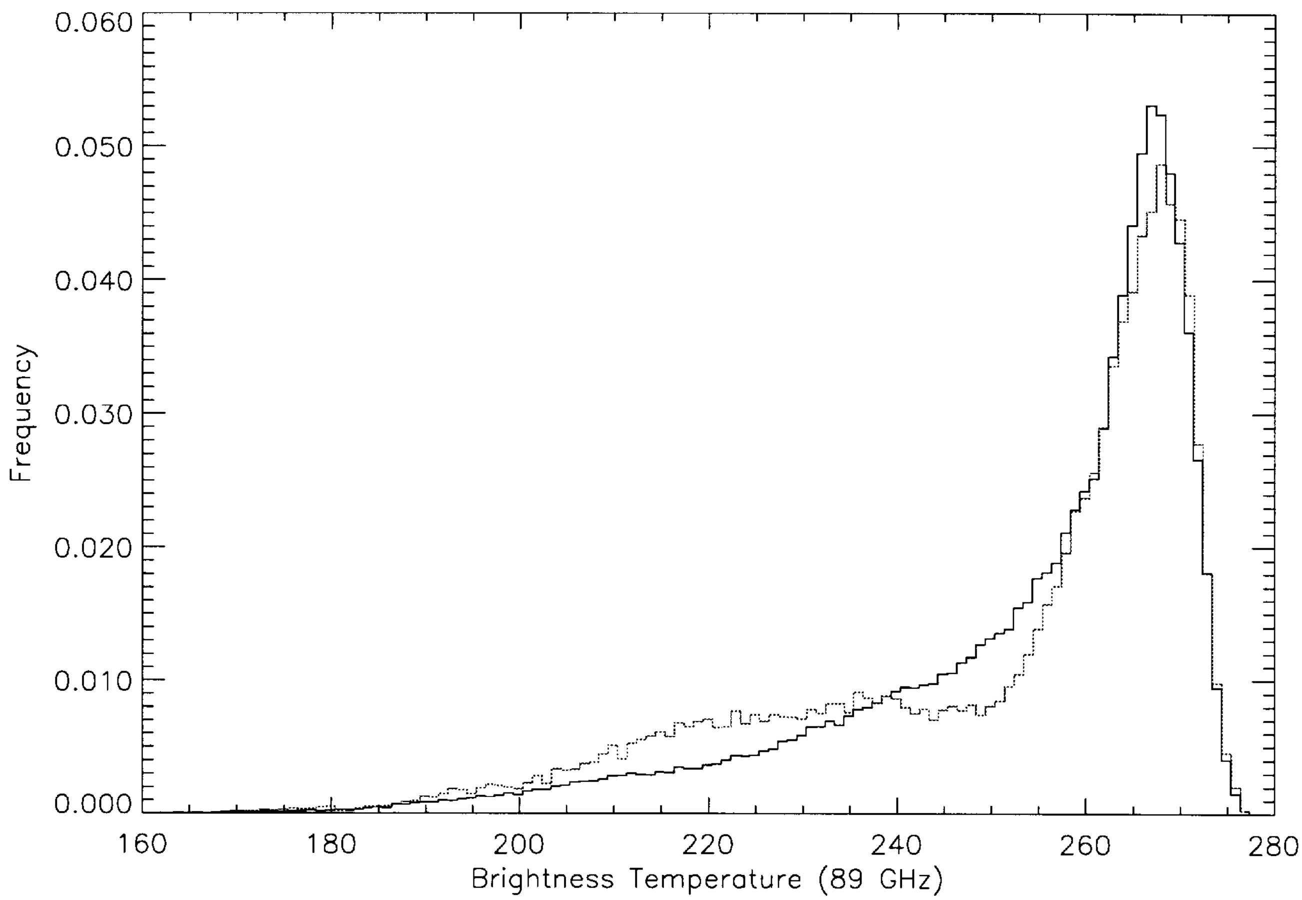
0.060
0.050
0.040
0.030
0.020
0.010
0.000
Frequency
160
180
200
220
240
260
280
Brightness Temperature (89 GHz)

Fig 11

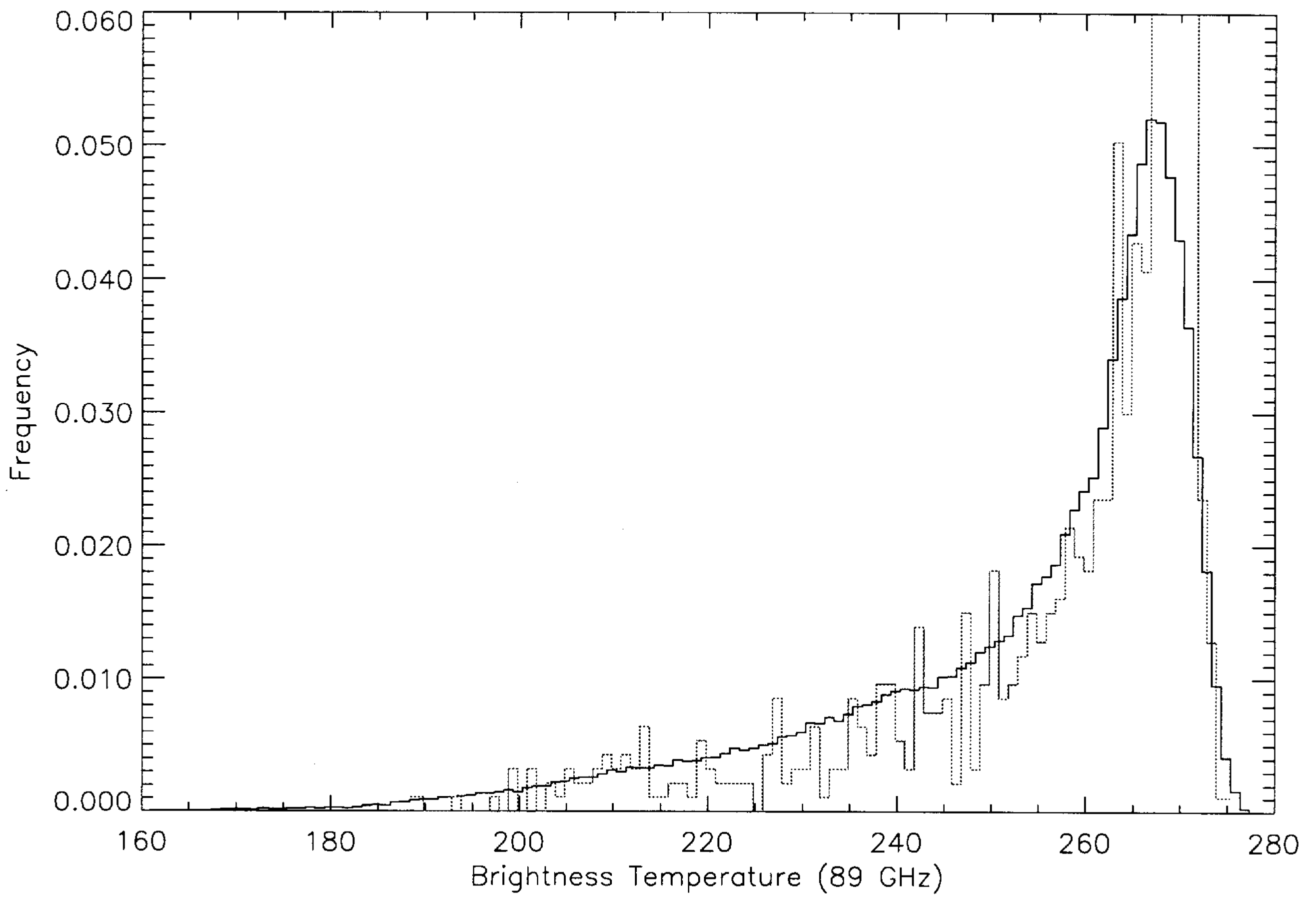
0.060
0.050
0.040
0.030
0.020
0.010
0.000
Frequency
160
180
200
220
240
260
280
Brightness Temperature (89 GHz)

Fig 12

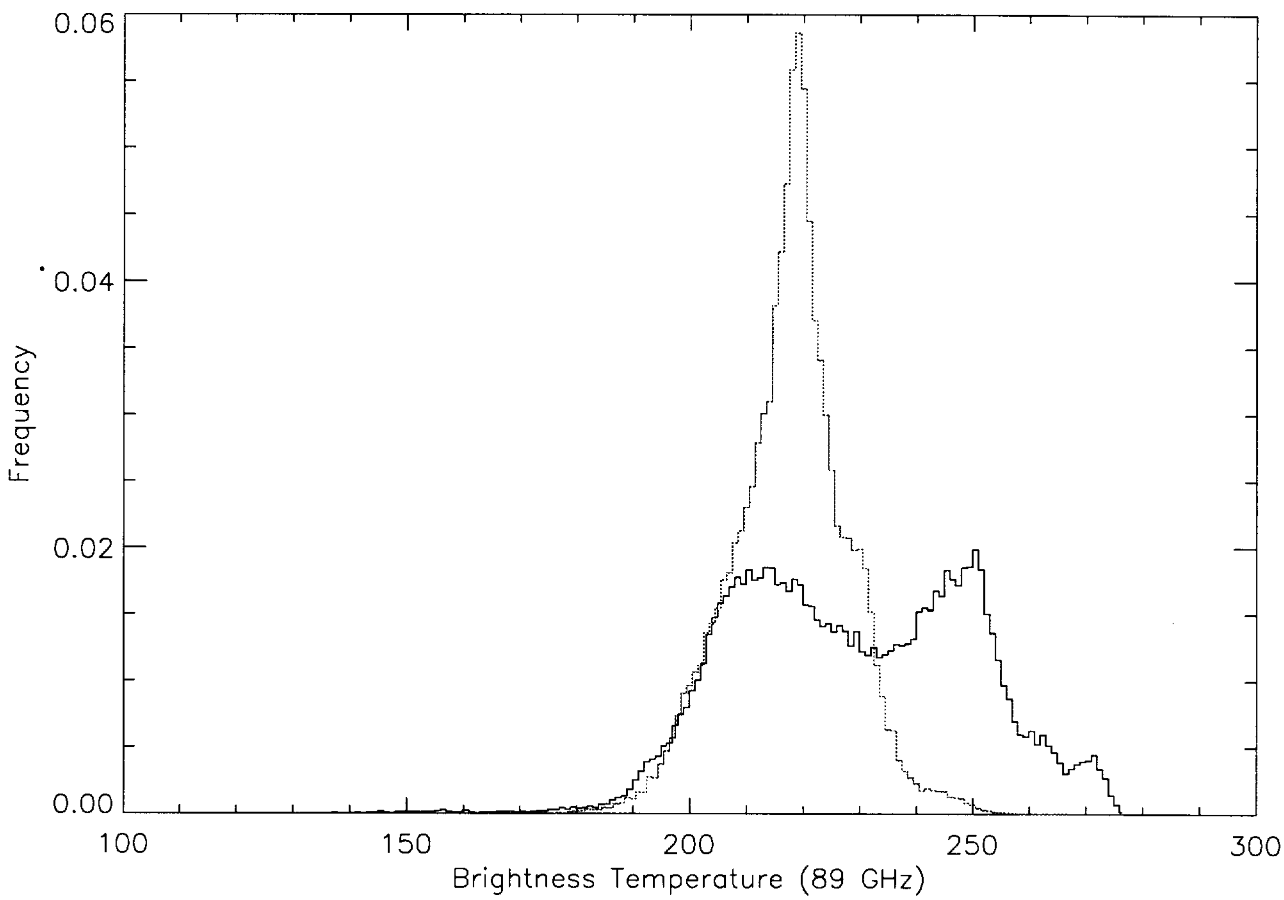
0.06
0.04
0.02
0.00
Frequency
100
150
200
250
300
Brightness Temperature (89 GHz)

Fig 13

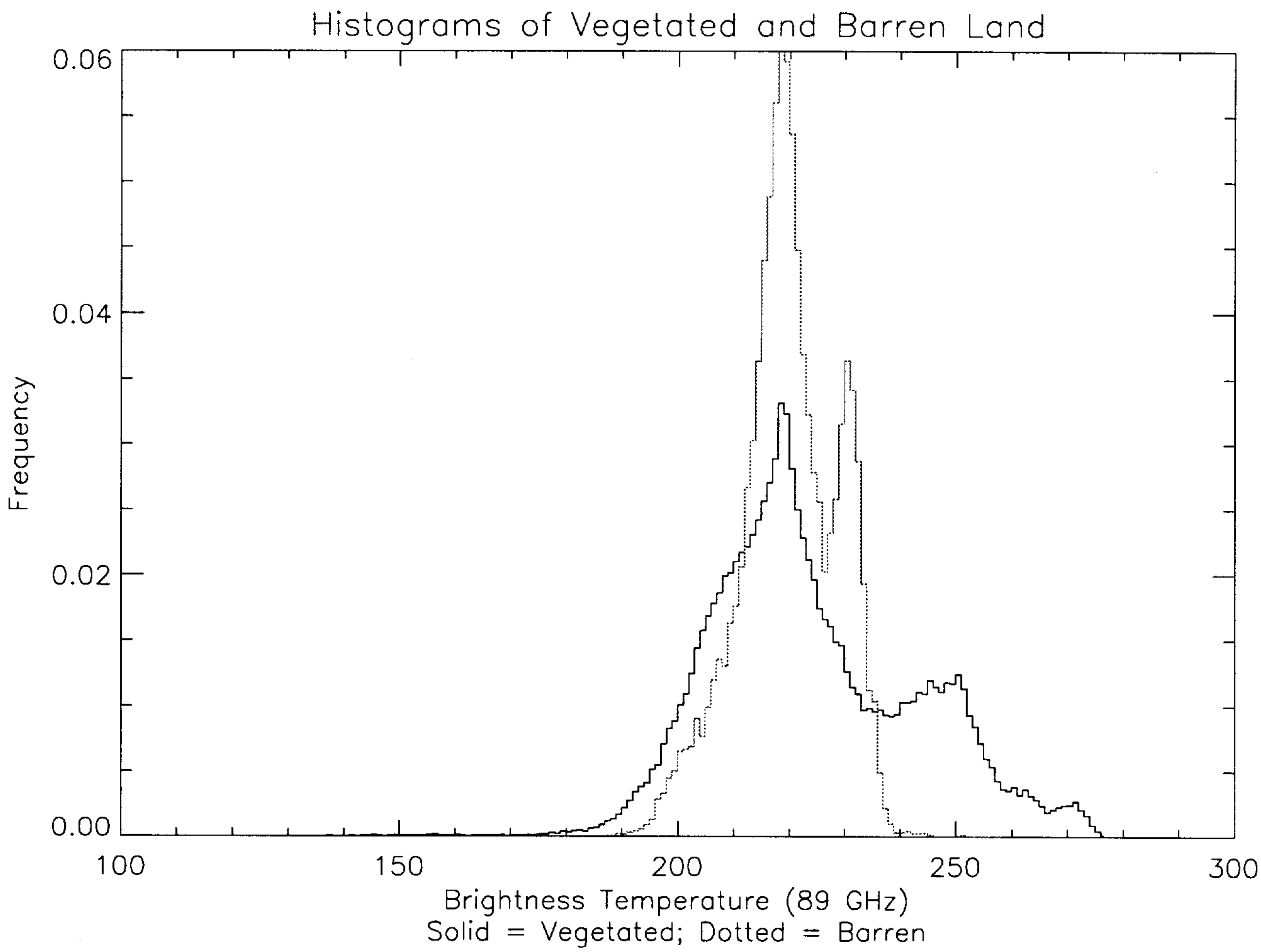
Histograms of Vegetated and Barren Land
0.06
0.04
0.02
0.00
Frequency
100
150
200
250
300
Brightness Temperature (89 GHz)
Solid = Vegetated; Dotted = Barren

Fig 4